

# IQGA: A route selection method based on quantum genetic algorithm- toward urban traffic management under big data environment

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## Abstract

The increasingly serious problem of traffic congestion has become a critical issue that urban managers need to focus on. However, as urban scale and structure have already taken shape, the use of existing road resources to achieve effective route selection for vehicles is the key to solving this traffic congestion problem. Existing research has mainly focused on the following three points: (1) algorithms for controlling traffic signal lamp period at single intersections; (2) route recommendation algorithms for a single vehicle; and (3) route recommendation algorithms based on the traffic history experienced by a vehicle. These studies, however, have the following limitations: (1) the evaluation factor is singular, and therefore, cannot fully express the advantages and disadvantages of the route selection method; (2) real-time route selection is absent; (3) route selection for a single vehicle is ineffective in avoiding local congestion. In view of these problems, this paper proposes an improved quantum genetic algorithm (*IQGA*) to solve the problem of traffic congestion in route selection. The algorithm includes the following: (1) proposing a quantum chromosome initialization strategy (*QCIS*) to convert and code real traffic conditions and to construct quantum chromosomes based on the quantum coding for vehicles and roads; (2) proposing a quantum chromosome mapping algorithm (*QCMA*) to transform the calculation bits of quantum chromosomes into the results of route selection for different vehicles; (3) proposing a contemporary optimal solution decision

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strategy (*COSDS*) to judge the current route selection results; (4) proposing a quantum update algorithm (*QUA*) to update and iterate the quantum coding of the population. Two types of experiments were conducted in this study: (1) Artificial traffic networks with different scales were designed to carry out comparative experiments between *IQGA* and other algorithms. The experimental results show that *IQGA* has better robustness and adaptive ability. (2) Comparative experiments on an actual urban traffic network verified the high-performance and real-time performance capabilities of *IQGA*.

**Keywords** Traffic congestion · Route selection · Multi-intersection · Chromosome mapping · Quantum genetic

## 1 Introduction

In addition to an increase in travel time, rising traffic congestions have also led to a number of negative socio-economic impacts such as an increase in energy consumption, increasingly frequent traffic accidents, noise pollution, environmental pollution, and increasing difficulty in management. Therefore, there is an urgent need to find a solution to traffic congestion. Since it is difficult to change existing urban traffic networks and increase existing road resources, the optimal way to solve the problem of traffic congestion is to make full use of existing road resources in order to achieve efficient route selection for operating vehicles [14, 31, 33].

At present, there are several main methods used to alleviate urban traffic congestion. The first method involves controlling traffic signal lamp time intervals at intersections to increase traffic transport capacity. This method mainly regulates the passage time at each section from a global viewpoint [32]. It increases the passage time at congested sections and reduces the passage time at spare sections to relieve traffic, but it does not take into account the demand characteristics of a single vehicle in the traffic network. The second method establishes a route selection algorithm for a single vehicle, that is, the shortest route optimization for a single vehicle can be used. The performance of this method is mainly determined by the shortest route optimization algorithm, which mainly includes the *Dijkstra* algorithm [16, 25], *A\** algorithm [1, 13], blind search [6], and ant colony algorithm [18, 38]. While these algorithms are able to meet the interests of individual vehicles, they are not able to take other vehicles in the same road network into consideration. In other words, they are unable to solve local traffic congestion and instead, they result in idle local road resources and may even cause further congestion. The third method utilizes a route selection algorithm based on the historical route of vehicles [28, 30]. This method establishes a database related to vehicle routes by means of a statistical method. When distributing the routes for vehicles, it will search the database for prior routes similar to the current traffic state combined with the current location of the vehicles and destination to distribute the requesting vehicles. While this method is suitable for small-scale urban traffic networks and plays a certain role in alleviating traffic congestion, it is difficult to use this method to fully consider the multitude of possible traffic conditions [48, 49]. Therefore, this method cannot be applied to large-scale urban traffic networks because it lacks flexibility and requires a huge workload since the database has to be updated in a timely manner [40, 45]. The fourth method is known as a dynamic traffic prediction model. This method provides route selection for vehicles in the traffic network through real-time road traffic information. The prediction models of traffic information include moving average (*MA*) models [10], auto regressive (*AR*) models [39], and auto regressive moving

average (ARMA) models [36]. Many prediction methods are also applied in the traffic planning domain, such as the *Kalman* filtering method [46], multiple regression method [24], neural network method [34], wavelet theory-based method [35], nonparametric regression model [23], Markov prediction, and grey prediction theory [2]. All the aforementioned methods can achieve short-term traffic flow predictions and provide route selection, but dynamic and real-time forecast models are so complex that the dynamic guidance scale is restricted [15, 27, 41]. Therefore, these methods are not sufficiently feasible, and further development and improvements are needed. In order to overcome the problems of a single evaluation index, lack of flexibility, and that global and individual characteristics cannot be unified in an existing route selection strategy, this paper constructs an enclosed global network model based on multiple vehicles and multiple routes and proposes a strategy that uses utility values to evaluate the route selection method. The utility values will be calculated by fully considering, and applying certain weights, to various possible factors that may affect the route choices of vehicles. In order to output utility values in real time for route selection, this paper introduces a quantum genetic algorithm (Sun and Ding, 2013; Yang, 2014), based on which an improved quantum genetic method *IQGA* (Improved Quantum Genetic Algorithm) is proposed to solve the problem of route selection in traffic congestion. Based on the superiority of quantum computing, the best utility value is calculated in real time, and an appropriate route selection scheme is obtained.

The main work of this paper includes the following aspects.

- (1) A real-time and dynamic multi-intersection route selection model is proposed, which synthetically considers the influence factors of urban traffic networks and integrates them into the utility value. The utility value is used to judge the advantages and disadvantages of the route selection scheme.
- (2) An evaluation model of the utility value is proposed in which the factors considered by vehicles during the selection of routes in a real traffic network are fully simulated. The results obtained are therefore more objective and realistic.
- (3) The *IQGA* method is proposed. It combines route selection with quantum chromosome coding and quantum updating and uses the high parallel computing characteristics of a quantum computer to obtain an iterative solution. Under the conditions of satisfying the individual preference, the global optimal route selection solution is obtained.

The remainder of this paper is organized as follows. Section 2 mainly introduces related research work. Section 3 introduces a closed city road network model, which includes the calculation of the utility value. Section 4 introduces the *IQGA* method. Section 5 verifies the validity of the *IQGA* method by experiments in artificial traffic network simulations and real traffic network cases. Finally, section 6 presents the conclusions of the study and future research.

## 2 Related works

To improve the effectiveness of traffic signal lamp control algorithms, Anastasios et al. [11] proposed a strategy for real-time traffic signal control, which was used to solve traffic signal control modes under non-peak and super saturation states. Kartik et al. [21] proposed an algorithm based on vehicle radio networks. It could group vehicles by collecting their current

positions and velocity information and control traffic signal lamps adaptively in real time to ensure minimum intersection delay among the vehicle groups. *He et al.* [8] proposed a steady-state signal control algorithm and a unified consensus clustering signal, which adjusted the signal to balance the network global load. This method could reduce local congestion and achieve a balanced distribution of traffic flow. *Yang Xu et al.* [42] proposed a distributed green wave adaptive control method based on multi-agent traffic lights, which made traffic flow increase through a non-centralized collaborative agent to control the traffic lights. However, the aforementioned methods mainly distributed vehicles from the overall traffic flow and did not take into account the personalized travel demand of individual vehicles [9, 29]. Besides, these methods could only alleviate traffic pressure to a certain extent but are ultimately incapable of relieving traffic congestion.

To solve the problem regarding the insufficient consideration of the characteristics of individual vehicles in urban traffic networks, *Shinsuke et al.* [17] proposed a route recommendation algorithm, which estimated driver intentions and then determined the optimal route according to those intentions. This method could estimate the intention of the driver through the analysis of selected routes and unselected routes, and thereby enlarge these differences and set parameters to obtain a modified optimal route. *Tomas et al.* [22] put forward a method of network segmentation. This method would first divide the traffic network into homogeneous clusters and heterogeneous clusters. In a homogeneous cluster, the method divided the traffic network into load-balanced sub networks. In a heterogeneous cluster, the method divided the traffic network into different sub networks by comparing the load ratio of the target node with that of a specific node and achieved route recommendations based on the weight values of these different sub networks [26, 44]. These aforementioned methods took full account of the preferred ratio of sections in the traffic network for drivers and the present load proportion of road sections from a microcosmic view [47], but they can easily cause local traffic congestion since a large number of vehicles can be potentially assigned to the same section.

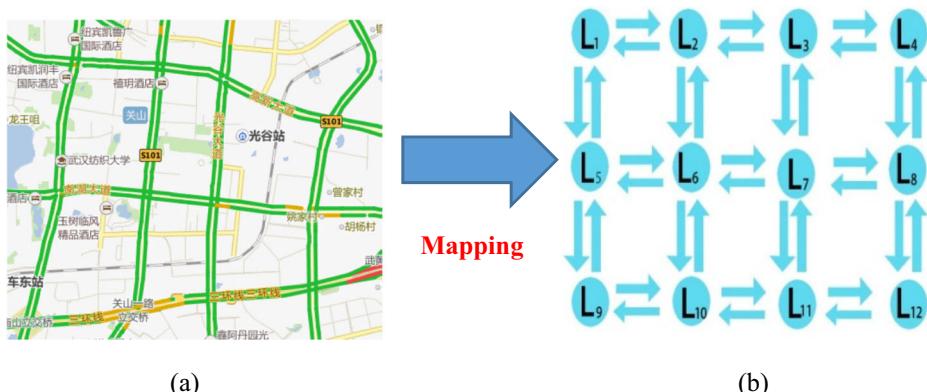
To relieve traffic congestion and achieve a global balanced load of an entire traffic network, *Kit et al.* [3] proposed an *APSO* algorithm based on swarm intelligence neural network short-term traffic flow prediction, which was combined with a neural network algorithm and had a positive effect on predicting traffic flow data with strong non-linear characteristics and newly captured traffic data. *Lee et al.* [12] proposed a vehicle coordination solution based on traffic control and traffic information acquisition through *VANET*. The proposed traffic aware routing protocol in this solution could monitor real-time traffic status of adjacent roads to deploy static nodes and to consider the traffic network flow. At the same time, the solution also delivered mixed traffic information to other result nodes to achieve mutual assistance among vehicles in order to select more powerful and efficient global optimal routes. *Yamada et al.* [43] proposed a route recommendation method based on hyper-route, which chooses a set of routes with the same driving time and recommended them to the vehicles on the basis of probability and dispersed the traffic flow on a group of similar routes, but this method is based on static historical data and not on real-time dynamic traffic information. *Pan et al.* [20] dispersed vehicles to routes that have low traffic flow as far as possible according to real-time traffic information but did not take full advantage of the actual shortest route capacity, which would cause some vehicles to embark on extremely long routes. *Wang et al.* [37] avoided emergent traffic congestion events by collecting real-time traffic information through traffic lights, and the vehicles would be evenly distributed throughout the entire road network. However, this study only considered traffic lights and the collaboration of relevant sections but did not consider the travel demands of individual vehicles.

In summary, the existing solutions to traffic congestion problems in urban road networks have several limitations such as a single evaluation index, an insufficient consideration of the characteristics of individual vehicles, and an absence of dynamic route selection, which easily leads to local congestion. The *IQGA* method proposed in this paper is a real-time route selection algorithm for solving traffic congestion based on a dynamic routing environment. It schedules vehicle routes dynamically through real-time calculations of the overall vehicle states and the congestion degree of the urban traffic network. Compared with existing route selection algorithms, the proposed method is more real-time and has a greater practical reference value. The simulation model in this study takes full consideration of the differences between individual vehicles and the impact that environmental factors have on vehicles. Under the premise of ensuring both global utilization maximization and individual differences, it provides the travel route for each individual vehicle, which is in line with its own characteristics.

### 3 System models

In view of the problem that multiple vehicles and multiple intersections were not considered in previous studies, this study proposes a real-time dynamic multi-intersection multi-vehicle urban traffic model, in which the number of intersections, sections, and vehicles are fixed. There are one-way sections and two-way sections in this urban road network model. Before starting the algorithm, the real network is mapped onto a directed graph.

As shown in Figure 1, a real traffic network (Figure 1a) is mapped onto a model graph  $G(L, E)$  (Figure 1b), where  $L$  is the set of all nodes and  $E$  is the set of all vector arrows showing the direction among nodes.  $L_i$  ( $i = 1, 2, 3, \dots, c$ ) represents a single intersection, where  $c$  is the total number of intersections. The sections in Figure 1a are mapped into vector arrows in Figure 1b.  $E_i$  ( $i = 1, 2, 3, \dots, r$ ) represents one side of the sections containing two intersections, where  $r$  is the total number of sections in the traffic network. For example,  $E_i = (L_s, L_t)$  ( $s, t \in \{1, 2, \dots, c\}$ ) indicates the section from the intersection  $L_s$  to the intersection  $L_t$ . All running vehicles in the traffic network are represented with a set  $V$ , and a single vehicle is represented by  $V_i$  ( $i = 1, 2, 3, \dots, n$ ), where  $n$  is the total number of vehicles. Each vehicle has a current position  $L_s$  and a current destination  $L_t$ . For vehicles between two intersections, its current position  $L_s$  is the



**Figure 1** Mapping of a real traffic network

intersection to which it is bound. For vehicles whose destinations are between two intersections, its current destination  $L_t$  is represented by the intersection closer to the destination. Therefore, for a vehicle  $V_i$  in the traffic network, its route can be represented by an intersection set; for vehicle  $V_i$  whose current position is  $L_s$  and whose destination is  $L_t$ , the route can be represented by an intersection set  $\{L_s, L_j, \dots, L_t\}$ . Therefore, a feasible route selection for  $V_i$  can be expressed as  $Route_{s_i,t} = \{L_s, L_j, \dots, L_t\}$ . Each vehicle in the traffic network is assigned a route, and the routes of all vehicles constitute a route selection, which can be represented by  $\{Route_{s_1,t_1}, Route_{s_2,t_2}, \dots, Route_{s_n,t_n}\}$ .

In this paper, the number of route selection schemes is large and we use the utility value  $F$  to evaluate whether the current route selection scheme is good. The scheme with the highest utility value is the optimal route selection scheme. There are many factors affecting the utility value, which include several constant factors such as the number of lanes, road speed limits, traffic lights, and the compliance of the driver to the recommended route selection scheme. There are also dynamic factors that change with time, such as the optional route distance, time consumption, and road conditions. The constant factors in this paper are integrated as the preference value  $Z$  and the dynamic factors are integrated as the cost value  $K$ . The formula for computing the utility value  $F$  is shown in Eq. (1).

$$F = Z - K \quad (1)$$

For a vehicle that has been assigned a route, its utility value is determined by the preference value  $Z$  and the cost value  $K$ , the calculation of which is determined by the actual road conditions. The influence factors of the preference value are shown in Table 1, and the influence factors of the cost value are shown in Table 2.

**Table 1** Influence factors and their descriptions of  $Z$

Influence factors	Range of values	Descriptions
$Z_r$	{0, 1}	$Z_r$ indicates whether the road section is reachable, where 1 indicates reachable and 0 indicates that it is not reachable. When $Z_r = 0$ , the preference value is set to -1, and the related utility value is not required to be computed.
$Z_m$	[0, 1]	$Z_m$ represents road conditions, such as the number of lanes and road surface roughness. The better the road condition is, the greater this value is.
$Z_s$	[0, 1]	$Z_s$ represents speed limit, such as the speed limit near schools and hospitals. Crosswalk number also has an impact on speed. The lower the speed limit, the greater $Z_s$ is.
$Z_\ell$	[0, 1]	$Z_\ell$ represents road lighting conditions. In the day, it is set as 1. At night, the better the lighting conditions are, the greater the value is.
$Z_\beta$	[0, 1]	$Z_\beta$ represents the extent to which the driver is obedient to the recommended route. The more he is willing to accept the recommended selection, the greater this value is.
$Z_w$	[0, 1]	$Z_w$ represents the degree of familiarity of the driver with the roads. The more familiar the driver is with the road, the greater this value is.

**Table 2** Influence factors and their descriptions of  $K$ 

Influence factors	Range of values	Descriptions
$K_a$	$[0, 1] \cup \{\text{INF}\}$	$K_a$ represents the impact of traffic accidents or temporary traffic control. The greater the degree of impact, the greater this value is. INF means that the road cannot be passed.
$K_t$	$(0, \infty)$	$K_t$ indicates the time cost of the selected route.
$K_d$	$(0, \infty)$	$K_d$ indicates the distance cost of the selected route.
$K_o$	$(0, \infty)$	$K_o$ indicates the oil consumption cost of the selected route.
$K_\ell$	$[0, 1]$	$K_\ell$ represents the influence of traffic lights. The longer the waiting time on the selected route because of traffic lights, the greater this value is.

The degree of influence of the various factors in Table 1 on the preference value is different. Each factor is given a corresponding weight according to the city size and route selection target. For any vehicle with a distributed route, its preference value is a determined value, and has nothing to do with the route selection schemes of other vehicles. The value is only related to road conditions and the starting and ending points of the vehicle. The calculation of the preference value  $Z$  is shown in Eq. (2).

$$Z = Z_r * (\epsilon_1 * Z_m + \epsilon_2 * Z_s + \epsilon_3 * Z_\ell + \epsilon_4 * Z_f + \epsilon_5 * Z_w) \quad (2)$$

where  $\epsilon_i (i=1, 2, \dots, 5)$  are independent multiplicative weights of the corresponding influence factors, and their values depend on the city scale and the policy-making goal. The greater the multiplication weight, the more important is the corresponding factor. For any vehicle in the traffic network, the weight value of each influencing factor on any road section is determined. Therefore, for an optional route for any vehicle, the preference value of each road section is determined, and the sum of the preference values of all road sections in a route is the preference value of this route. The greater the preference value of the route, the better is the route.

The calculation of the cost value is relatively complex, because there are some correlations between various influence factors of the cost value. For a certain road section, the time cost  $K_t$  and the oil cost  $K_o$  are not only affected by the travel distance, but are also related to the current road congestion state. In general, before the number of vehicles reaches the normal road capacity on a road section, the time cost and oil cost are fixed for a vehicle. When the number of vehicles is between the normal road capacity and the road congestion capacity, both the time cost and the oil cost change linearly with the number of vehicles. After reaching the congestion capacity, the growth in the number of vehicles will cause the time cost and the oil cost to grow exponentially. In this paper, we use the congestion factor  $\gamma$  to describe the relationship between the time cost  $K_t$  and the oil cost  $K_o$  and the number of vehicles on the road section. Equation (3) shows the calculation method for the congestion coefficient  $\gamma$ . The threshold of the road section is given by  $H$ , the traffic congestion of the road section is  $R$ , and the current number of vehicles on the road section is given by  $x$ .

$$\gamma = \begin{cases} 1, & x < H \\ \frac{x}{H}, & H \leq x < R \\ \frac{R}{H} + e^{\frac{x}{R}}, & R \leq x \end{cases} \quad (3)$$

When the congestion coefficient  $\gamma$  of a road section is determined, the time cost  $Kt$  and the oil cost  $K\sigma$  are determined correspondingly. When the route selection schemes of all vehicles are determined, the cost of any route  $K$  is determined, the calculation of which is shown in Eq. (4).

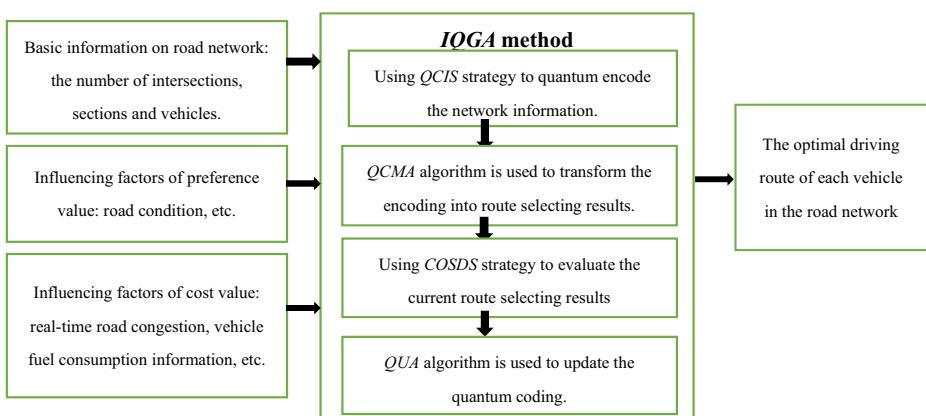
$$K = \omega_1 * K\alpha + \omega_2 * Kt + \omega_3 * Kd + \omega_4 * K\sigma + \omega_5 * Kl \quad (i = 1, 2, \dots, r) \quad (4)$$

where  $\omega_i (i=1, 2, \dots, 5)$  are independent multiplicative weights of the corresponding cost influence factors, and their values depend on the city scale and the policy-making goal. Their values respectively represent the impact degree of each influence factor on the cost value. For any vehicle in the road network, the smaller the cost value  $K$  of the selected route, the better the route. The sum of the cost values of all sections of the route is the cost value of the route.

In our proposed algorithm, it is the sum of all the utility values of all vehicles in the traffic network that is used to judge whether the route selection was good. Thus, for a single vehicle in the traffic network, there may be a route that is “globally optimum but locally the poorest.” To ensure individual interests, optional routes for individual vehicles in our algorithm are selected within the tolerance limits of the drivers.

#### 4 Route Selection Method based on Quantum Genetic Algorithm

In this paper, there are two relationships between a certain vehicle and a road section in the road network model: the vehicle either passes through the section or does not. Both relationships can be expressed by two quantum ground states: state  $|0\rangle$  expresses that the vehicle does not pass through the section, state  $|1\rangle$  expresses that the vehicle passes through the section. Based on the premise of the quantum encoding of the vehicle and the route, the proposed *IQGA* method uses the quantum chromosome initialization strategy (*QCIS*) to quantify and encode the quantum chromosome of the actual traffic condition. Then, it uses the quantum chromosome mapping algorithm (*QCMA*) to transform the quantum chromosomes into route selection results for different vehicles. The contemporary optimal solution decision strategy (*COSDS*) is used to judge the performance of the current route selection, and the quantum updating algorithm (*QUA*) is used to update the quantum coding of the population. The algorithm flow of the improved route selection method based on this quantum genetic algorithm is shown in Figure 2.



**Figure 2** Method framework of *IQGA*

#### 4.1 Quantum Chromosome Initialization Strategy

This study uses quantum genetic encoding to encode road sections based on vehicles, and the relationship between a vehicle and each section is represented by a qubit. Quantum genetic algorithm is carried out simultaneously on multiple populations, and each population corresponds to a route selection scheme. When the number of populations is bigger, the complexity of the population gene is higher, and the possibility of getting an optimal solution is greater. The specific implementation can be adjusted according to the size of the problem to be solved. In this paper, the number of populations is set as  $m$ ; the value of  $m$  is determined by the scale of the road network and the number of road sections. When using qubits for encoding, the quantum chromosome encoding scale for a single car is  $2r$ , and the size of the population of the quantum chromosome encoding is  $2n \times r$ . Combined with the number of populations, the size of the quantum chromosome encoding for one computation is  $2m \times n \times r$ . The quantum chromosome encoding of a single vehicle is denoted as  $U$ , which is shown in Eq. (5):

$$U = \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 & \dots & \alpha_n \\ \beta_1 & \beta_2 & \beta_3 & \dots & \beta_n \end{bmatrix} \quad (5)$$

For an urban road network, the scales of the road network and the vehicles are both large, such that a classical computer cannot satisfy the requirements of data storage and computing. Quantum computers have powerful storage capacities and computing power, so we propose implementing the proposed algorithm on a quantum computer. In a quantum computer, each qubit can be in a state of superposition. For a quantum register with  $N$  bits, the state of superposition can be expressed as shown in Eq. (6):

$$|\psi\rangle = |q_0\rangle \otimes |q_1\rangle \otimes \dots \otimes |q_{N-1}\rangle \quad (6)$$

$|\psi\rangle$  is a unit vector in the Hilbert space with  $N$  dimensions; it has  $2^N$  basic states of mutual orthogonality, which is expressed in Eq. (7).

$$|\psi\rangle = \sum_{i=0}^{2^N-1} \alpha_i |i\rangle, \quad (7)$$

where  $\sum_{i=0}^{2^N-1} \alpha_i^2 = 1$ , which shows that in a quantum computer the number with  $N$  bits in the state of superposition can be represented by  $2^N$  integers from 0 to  $2^N - 1$ , and each of them exists at the same time with a certain probability. Therefore, an  $N$ -bit quantum register can store  $2^N N$ -bit binary numbers. The linear increase of the bits in the quantum register allows the storage space to experience exponential growth. At the same time, the quantum computer can use a quantum gate to operate  $N$  qubits in quantum computing so that the computing efficiency is far beyond that of a classical computer.

To increase the diversity of the population and reduce the number of operations at the initialization of coding the population, this paper adopts the coding method combined with the number of vehicles on the route. For each vehicle  $V_i (i = 1, 2, \dots, n)$  in the population  $P_i (i = 1, 2, \dots, m)$ , the initializing code method can be expressed as follows. For the quantum chromosome from the segment  $\frac{r^*(i-1)}{m}$  to the segment  $\frac{r^*i}{m}$  of  $V_i$ , state  $|0\rangle$  can be encoded as  $\sqrt{x/L}$ , and state  $|1\rangle$  can be encoded as  $\sqrt{1-x/L}$ . For the quantum chromosomes of the other segments of  $V_i$ , state  $|1\rangle$  can be encoded as  $\sqrt{x/L}$ , and state  $|0\rangle$  can be encoded as  $\sqrt{1-x/L}$ .

This coding method can ensure the diversity of the population, and is able to avoid local optimal solutions as far as possible so that a global optimal solution can be realized. The *QCIS* strategy is given in Table 3.

## 4.2 Quantum Chromosome Mapping Algorithm

Each quantum population corresponds to a route selection strategy, and each vehicle in the population will obtain the only route from the origin to the destination. When the quantum chromosome  $Bm^j$  ( $j$  is the current iteration number) is mapped into the route selection result, the principles of maximum selection and backtracking are followed, and the chromosome code is modified in the process of backtracking.

**Mapping principle: The maximum selection principle** When the vehicle  $V_i$  runs from intersection  $L_i$  to intersection  $L_j$ , it needs to select the turning direction at intersection  $L_j$ . At this time, all the intersections adjacent to  $L_j$  are marked as an intersection set  $Ll_j$ , and the end intersection of the section with the maximum probability amplitude of states  $|1\rangle$  in quantum chromosomes is selected as the next running intersection direction.

**Mapping principle: Backtracking correction** When  $L_w$  exists in the selected intersection set  $Route_{s,i}^j$  of vehicle  $V_i$ , vehicle  $V_i$  should backtrack to reselect the next running intersection. At this time, the maximum selection principle is no longer followed to select the intersection, the section with the maximum probability amplitude of states  $|0\rangle$  in  $Ll_j$  is selected as the next running intersection direction. Further, the probability amplitude of the section with the maximum one of states  $|0\rangle$  in  $Ll_j$  is exchanged with that of the section with the maximum one of states  $|1\rangle$  in  $Ll_j$ .

These two mapping principles can maximize the use of existing data and do not require the abandonment of existing chromosomes to build new ones, and instead, the chromosomes just need to be modified. They can ensure the correlation between chromosomes and improve the efficiency of computing and conversion. The *QCMA* algorithm is detailed in Table 4.

## 4.3 Contemporary Optimal Solution Decision Strategy

When the route selection strategies of the quantum population at each iteration are computed, they need to be judged according to utility  $F$ , whose computation process is detailed in Section 3. The sum of each individual's utility comprises of the utility of the current quantum

**Table 3** *QCIS* strategy

### *QCIS* strategy

Input: number of sections in the road network  $r$ , number of vehicles in the road network  $n$ , number of intersections in the road network  $c$ , and number of quantum populations  $m$

Output: Initializing quantum chromosome in quantum population  $Bm$

1. Determining the corresponding relationship between the section and intersections in the road network  
 $E_j = (L_s, L_j)(s, t \in \{1, 2, \dots, c\})$
2. Determining the encoding method for each segment of the quantum chromosome of each vehicle
3. Assigning and encoding the quantum chromosome in accordance with the selected encoding method
4. Outputting the initializing quantum chromosome  $Bm$  after encoding

**Table 4** QCMA algorithm**QCMA algorithm**

Input: quantum chromosome  $Bm^j$ , number of vehicles in the road network  $n$ , and number of quantum populations  $m$

Output: Initializing quantum chromosome in quantum population  $m$ , current intersection of a vehicle  $L_s$ , and destination intersection of a vehicle  $L_t$

1. For the  $k^{th}$  vehicle  $V_{h,k}$  in the  $h^{th}$  quantum population, the current intersection  $L_s$  and the approaching intersection into the selected intersection set  $Route_{h,k}^j$  are added;
2. According to the quantum chromosome  $Bm^j$  and the maximum selection principle, the next approaching intersection  $L_z$  of the vehicle  $V_{h,k}$  is selected;
3. If  $L_z$  is the destination intersection  $L_t$ , the set  $Route_{h,k}^j$  is outputted as the selected intersection result of the vehicle  $V_{h,k}$  in the  $h^{th}$  quantum population at the  $j^{th}$  iteration;
4. It is judged whether  $L_z$  exists in the set  $Route_{h,k}^j$ . If it exists, step 5 is executed; if not,  $L_z$  is added into the set  $Route_{h,k}^j$  and step 2 is executed to continue the process;
5. According to the quantum chromosome  $Bm^j$  and the backtracking principle, reselect the next approaching intersection  $L_z$  of the vehicle  $V_{h,k}$  is reselected and step 3 is executed to continue the process.

population. The optimal utility at the current iteration is obtained through comparing the utilities of all the populations at the current iteration. The optimal utility at all iterations is obtained through comparing the optimal utility of the current iteration with that of the parent iteration. The quantum chromosome with the optimal utility is stored in the optimal chromosome set  $BestBm^j$ , and the optimal utility is stored in the optimal utility set  $BestF^j$ . At the same time, the quantum chromosome with the worst utility is stored in the worst chromosome set  $WorstBm^j$ , and the worst utility is stored in the worst utility set  $WorstF^j$ . In summary, the COSDS strategy is shown in Table 5.

#### 4.4 Quantum Updating Algorithm

When the judging of a route selection strategy is completed, the quantum chromosome populations are updated through quantum transformation gates, which include NOT gates, revolving gates, and *Hadamard* gates. In this paper, we adopt the revolving gate to update the quantum chromosome, the mathematical expression of which is shown in Eq. (8).

$$\begin{bmatrix} \alpha_{g,l}^{j+1} \\ \beta_{g,l}^{j+1} \end{bmatrix} = U(\delta\theta) \begin{bmatrix} \alpha_{g,l}^j \\ \beta_{g,l}^j \end{bmatrix} = \begin{bmatrix} \cos(\delta\theta) & -\sin(\delta\theta) \\ \sin(\delta\theta) & \cos(\delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_{g,l}^j \\ \beta_{g,l}^j \end{bmatrix} \quad (8)$$

where  $\delta\theta = g(\alpha, \beta) * \theta$ .  $g(\alpha, \beta)$  denotes the revolving direction, whose function is to restrict the convergence of algorithms and whose value can be obtained by querying Table 6.  $\theta$  denotes the revolving angle, whose function is to restrict the convergence speed of algorithms. In the traditional quantum genetic algorithm, the value of  $\theta$  changes with the iteration number. Although a change in this value can speed up the iteration to some extent and avoid premature falling into local optimal solutions, it does not change dynamically with the change of the quantum chromosomes. In this paper, the method to obtain  $\theta$  will be described in detail after the selection strategy of the rotation direction is introduced.

In Table 6,  $X(g, \ell)$  denotes the value of the  $\ell^{th}$  bit of the quantum chromosome for the  $g^{th}$  vehicle at the current iteration. If the  $g^{th}$  vehicle passes the  $\ell^{th}$  section,  $X(g, \ell)$  takes  $|1\rangle$  state; or else it takes  $|0\rangle$  state.  $b(g, \ell)$  denotes the value of the  $\ell^{th}$  bit of the optimal quantum

**Table 5** COSDS strategy**COSDS strategy**

Input: route selecting of all quantum populations at the  $j^{th}$  iteration  $Route^j$ , number of quantum populations  $m$ , number of vehicles in the road network  $n$ , and iteration number  $j$

Output: the optimal utility set  $BestF^j$ , the optimal chromosome set  $BestBm^j$ , the worst utility set  $WorstF^j$ , and the worst chromosome set  $WorstBm^j$

1. It is judged whether  $j$  is the maximum iteration number. If it is, the algorithm is terminated, and the current route selection strategy  $Route^j$  is outputted as the operation result of the algorithm, which is sent to the vehicles; if not, step 2 is executed;
2. The preference value  $Z_i^j$  and cost value  $K_i^j$  of the selected route for each vehicle are computed. If  $Z_i^j < Zy_i$  or  $K_i^j > Zy_i$ , the quantum chromosome corresponding to the current selected route is abandoned, and a new quantum population based on the QCIS strategy is generated; if not, the utility  $F_i^h$  is computed based on the formulas (1), (2), (3), (4);
3. The utilities of the vehicles in each quantum population are summed, and through comparison, the optimal utility  $Fb^h$  at the current iteration is obtained;
4.  $Fb^h$  is compared with the last element in the optimal utility set  $BestF^j$ . If  $Fb^h$  is bigger, the size of  $BestF^j$  is increased by one and  $Fb^h$  is added to the set  $BestF^j$ . At the same time, the size of the optimal chromosome set  $BestBm^j$  is increased by one, and the quantum chromosome corresponding to  $Fb^h$  is added to the set  $BestBm^j$ ; if not, the size of  $BestF^j$  is increased by one, and the second last value is copied to the last, and the size of the optimal chromosome set  $BestBm^j$  is increased by one and the second last value is copied to the last;
5. Through comparison, the worst utility  $Fw^h$  at the current iteration is obtained. The size of the worst utility set  $WorstF^j$  is increased by one, and  $Fw^h$  is added to the set  $WorstF^j$ . At the same time, the size of the worst chromosome set  $WorstBm^j$  is increased by one, and the quantum chromosome corresponding to  $Fw^h$  is added to the set  $WorstBm^j$ ;
6. The optimal utility set  $BestF^j$  and the optimal chromosome set  $BestBm^j$  are outputted.

chromosome for the  $g^{th}$  vehicle at the current iteration. If the  $g^{th}$  vehicle passes the  $\ell^{th}$  section,  $b(g, \ell)$  takes  $|1\rangle$  state; or else it takes  $|0\rangle$  state.  $f(x)$  denotes the preference value of the  $g^{th}$  vehicle in the current population for the planning route.  $f(b)$  denotes the optimal preference value at the current iteration. For example, when  $X(g, \ell)=1$ ,  $b(g, \ell)=0$ , and  $f(x) < f(b)$ , the probability range of the current solution for the  $g^{th}$  vehicle passing the  $\ell^{th}$  section should be increased through quantum gates so that the algorithm converges to the optimal solution. By referring to Table 6, we get that the rotation direction  $g(\alpha, \beta) = -1$ .

The range of chromosome initialization determines the probability that the algorithm may be iterated to the actual optimal solution to a certain extent. The method regarding how  $\theta$  is obtained directly determines the convergence speed of the algorithm and the probability of obtaining the global optimal solution. In this algorithm, the calculation of the iteration step size is used to calculate the angle of rotation. When the probability range of the  $k^{th}$  vehicle of the  $h^{th}$  population at the  $j^{th}$  iteration on the  $\ell^{th}$  section is updated, the angle of deviation from  $|1\rangle$  state is calculated by the probability amplitude of the corresponding  $|1\rangle$  state, which is denoted by  $Ang_{k,\ell}^h$ . The angle of deviation from  $|1\rangle$  state for the  $k^{th}$  vehicle corresponding to the optimal chromosome on the  $\ell^{th}$  section is denoted by  $Ang_B$ . The angle of deviation from  $|1\rangle$  state for

**Table 6** Lookup table of revolving gate

X( $\mathcal{G}, \ell$ )	b( $\mathcal{G}, \ell$ )	f(x) < f(b)	g( $\alpha, \beta$ )			
			$\alpha \cdot \beta > 0$	$\alpha \cdot \beta = 0$	$\alpha = 0$	$\beta = 0$
0	0	F	0	0	0	0
0	0	T	0	0	0	0
0	1	F	0	0	0	0
0	1	T	-1	+1	$\pm 1$	0
1	0	F	-1	+1	$\pm 1$	0
1	0	T	+1	-1	0	$\pm 1$
1	1	F	+1	-1	0	$\pm 1$
1	1	T	+1	-1	0	$\pm 1$

the  $k^{th}$  vehicle corresponding to the worst chromosome on the  $\ell^{th}$  section is denoted by  $Ang_w$ . The angle of deviation from  $|1\rangle$  state is computed in Eq. (9).

$$Ang = \cos^{-1} \alpha \quad (9)$$

Thus, the calculation formula for the rotation angle  $\theta$  is expressed as shown in Eq. (10).

$$\theta = Ang_{k,\ell} - sgn(Ang_B - Ang_{k,\ell}) * data * \exp\left(-\frac{\text{abs}(Ang_{k,\ell} - Ang_B - Ang_w)}{Ang_w - Ang_B}\right) \quad (10)$$

where  $data$  denotes the initial iteration angle, and its general value ranges from  $0.01\pi$  to  $0.03\pi$ .

The QUA algorithm is shown in Table 7.

## 5 Experiments and Analysis

To verify the effectiveness and robustness of the *IQGA* method in traffic simulation optimization problems, experiments were carried out on a simulated road network and a real road network to verify the effectiveness of the proposed algorithm. In section 5.1, the experimental environment and the contrast algorithms in our experiments are introduced, and classical computers are used to simulate the parallel computing process of quantum computers. In section 5.2, the experimental conditions and experimental results are introduced, and the effectiveness and robustness of the *IQGA* method are verified by setting a different number of intersections and a different number of vehicles. In section 5.3, the effectiveness and robustness of the *IQGA* method in different traffic density scenarios are verified in the real urban road network of the Wuchang District in Wuhan City.

### 5.1 Experimental Environments

Owing to the limitations of the current quantum computer experiment environment, this paper simulates the parallel computing process of quantum computers with classical computers. The quantum chromosome coding of a route is transformed into a three-dimensional matrix, and the route selection result is transformed into a two-dimensional matrix. The quantum update iteration process is represented by matrix multiplication. Since a classical computer is

**Table 7** QUA algorithm**QUA strategy**

Input: quantum chromosome  $Bm^j$ , number of quantum populations  $m$ , number of vehicles in the road network  $n$ , road sections in the road network  $r$ , the optimal chromosome set  $BestF^j$ , and the worst chromosome set  $WorstF^j$   
 Output: new quantum chromosome  $Bm^{j+1}$

1.  $k = 1, \ell = 1;$
2. while  $k \leq n \{$
3.     while  $\ell \leq r \{$
4.         The location of the quantum chromosome to be updated in the quantum chromosome group  $Bm_{k,\ell}^j$ , is determined, and the values of  $BestF_{k,\ell}^j$  and  $WorstF_{k,\ell}^j$  at the corresponding position are found;
5.         The corresponding deviation angles of each quantum chromosome group  $Ang_{k,\ell}^h, Ang_w, Ang_B$  are computed.
6.         The rotation angle  $\theta$  of the current quantum chromosome based on the values of the deviation angles is computed;
7.         The direction of the revolving gate is determined by referring to Table 6. The value of  $U(\delta\theta)$  is determined.
8.         The value of the corresponding chromosome  $Bm_{k,\ell}^j$  is determined.
9.          $\ell++;$      }
10.         $k++;$      }
11.      $j++;$
12. The updated quantum chromosome  $Bm^j$  is outputted.

considerably slower in parallel computing speed as compared to that of a quantum computer, the experimental results are expressed as an increase in the ratio of the utility value against that obtained by statistical methods, without considering the difference in the running time of each algorithm. When the network scale is small, a small number of vehicles can cause the road to reach a state of congestion. When the network scale becomes larger, the number of required vehicles to cause congestion also increases, but the increased vehicles have no influence on the verification of our algorithm. Therefore, in our experiments, the vehicle selection routes are set constant, and the increased vehicles with the expansion of the road network are set as the inherent ones, which are only involved in the calculation of the road congestion coefficient, but not in the calculation of route selection.

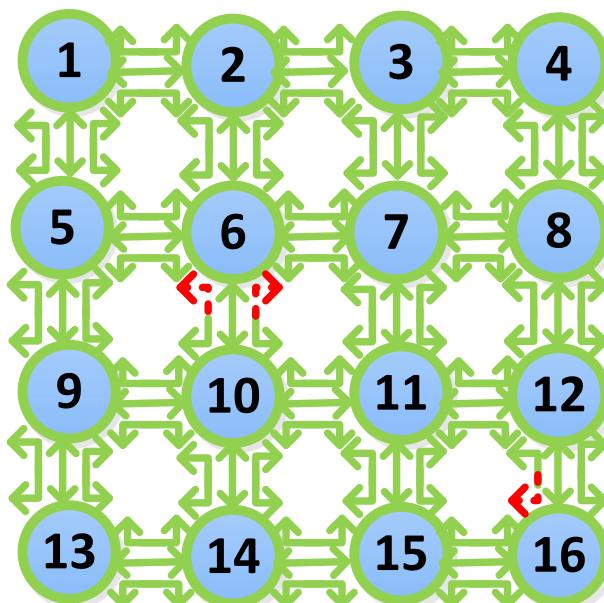
To verify the effectiveness of our approach, we selected some state-of-the-art comparison algorithms [4, 5, 7], including three non-cooperative algorithms and two equilibrium algorithms. The former three algorithms include a preference-based algorithm (*PA*), a shortest path algorithm (*SPA*), and a preference-based shortest path algorithm (*PSPA*). These algorithms only consider the preferences of vehicles, or their cost, or both the preference and cost, which form only a single evaluation index without a comprehensive consideration of many other factors that affect route selection. The two equilibrium algorithms include a Wardrop equilibrium algorithm (*WEA*) [19] and a reverse Stackelberg game approach (*RSGA*) [7]. These two algorithms can minimize the average cost for the driving vehicle, but they have a limitation on

scale, and are unable to provide real-time navigation on a large-scale urban road network. In our experiments, the proposed *IQGA* was compared with these five algorithms in different scales of artificial road networks and real road networks, and its effectiveness is verified through decreases in the percentages of travel time.

## 5.2 Artificial Road Network

This scenario selects an area of the artificial network as the experimental objective, which contains sixteen intersections and a number of two-way roads, as shown in Figure 3. Each driving vehicle has several routes to be selected based on its current starting point and destination. The length, traffic condition, speed limitation, and the average speed based on the real-time traffic density of each road section can be obtained. When all vehicles have determined their selected routes, the time cost, oil cost, and distance cost are determined correspondingly, and the utilities of all routes can be computed, among which the optimal route selecting scheme can be found.

To observe the performance of *IQGA* in different scales, the urban traffic network was scaled up to 16 ( $4 \times 4$ ), 100 ( $10 \times 10$ ), 400 ( $10 \times 10$ ), 10,000 ( $100 \times 100$ ) intersections. The latter three scales were obtained based on the expansion of the urban traffic network shown in Figure 3. In each simulation scenario with a fixed number of intersections, we designed five cases: (1) the number of vehicles was less than the threshold value of the road capacity (three sample values); (2) the number of vehicles was equal to the threshold value of the road capacity (one sample value); (3) the number of vehicles was greater than the threshold value and less than the congestion capacity (three sample values); (4) the number of vehicles was equal to the congestion capacity (one sample value); (5) the number of vehicles was greater than the congestion capacity (three sample values). The simulation was run with the same

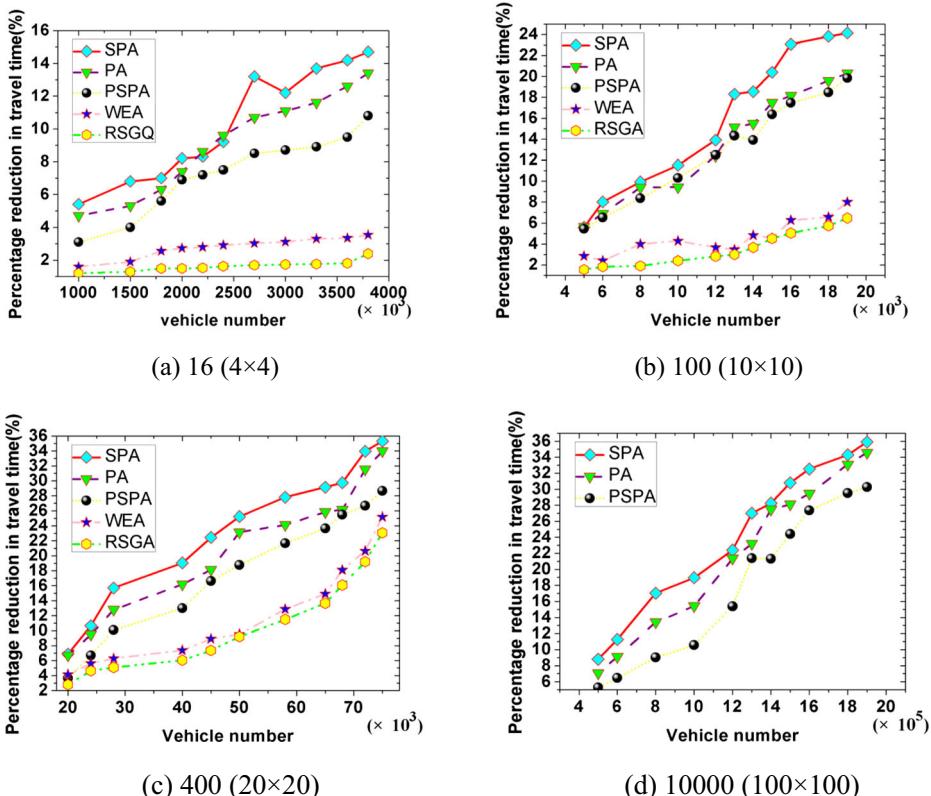


**Figure 3** An artificial urban traffic network with 16 intersections

traffic conditions as the real urban traffic network, including traffic conditions on each road section, vehicle distribution, and the starting point and destination of each vehicle. In different scales with different intersections, the percentages of the decrease in travel time of *IQGA* over the three non-cooperative algorithms and two state-of-the-art equilibrium algorithms are shown in Figure 4.

From Figure 4, we can draw the following conclusions.

- (1) The greater the number of vehicles in the road network and the greater the amount of traffic congestion, the greater the utility value computed by *IQGA* and the more obvious the percentages of the decrease in travel time using *IQGA* relative to the other five comparison algorithms. When the number of vehicles was increased, the travel time using *IQGA* compared with those obtained using the five different algorithms have different degrees of decline. This indicates that *IQGA* is more suitable than the other five algorithms for route selection for different numbers of vehicles. From Figure 4c, it can be seen that when the number of vehicles and intersections reach a certain level, *IQGA* as compared with three single evaluation index algorithms (*PA*, *SPA*, *PSPA*) reduces travel time by 18% or more, and when compared with the two equilibrium algorithms (*WEA*, *RSGA*), it reduces travel time by more than 12%. When the number of



**Figure 4** the percentages of the decrease in travel time of *IQGA* over the three non-cooperative algorithms and two state-of-the-art equilibrium algorithms in artificial urban networks

vehicles is near the limit capacity of the road network, *IQGA* has more obvious advantages. This is because the coordination and cooperation between vehicles is more important in a congested road network. *IQGA* considers the interests of each vehicle in the road network, allowing it to not only make full use of the existing road resources, but also effectively solve the problem of local congestion. *PA*, *SPA*, *PSPA* algorithms only focus on the maximization of the interests of a single vehicle, so when the number of vehicles and the scale of the road network continues to increase, they are unable to coordinate the interests of a large number of vehicles, resulting in local congestion. When the scale of the road network reaches the size of Figure 4d, the complexity of *WEA* and *RSGA* algorithms increases, and thus, it is difficult to achieve a balanced distribution of vehicles. On the other hand, *IQGA* can achieve the obvious effect of quantum parallel distributed computing.

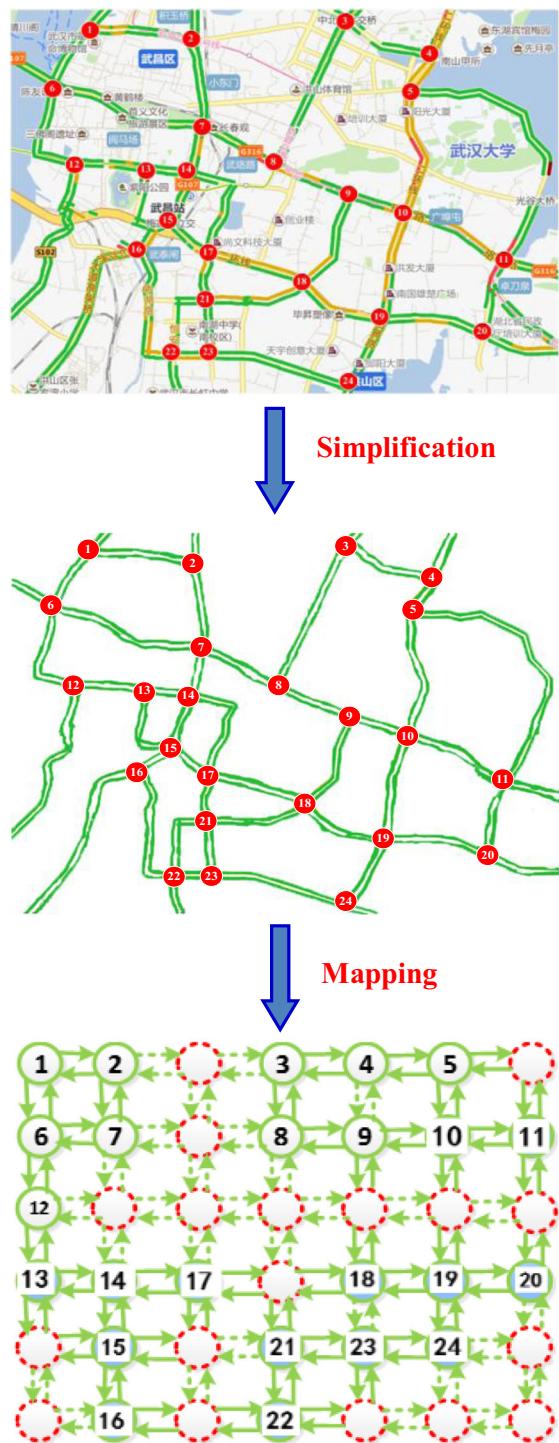
- (2) When the number of intersections is small as shown in Figure 4a, there was almost no difference between the performances of *IQGA* and the two equilibrium algorithms, *WEA* and *RSGA*, and the percentage of the decrease in travel time is less than 1%. However, when the scale of the road network was increased, the performance of *IQGA* as compared with those of *WEA* and *RSGA* was improved by more than 10%, which shows that *IQGA* has better adaptability to road network scales. Regardless of the number of intersections in the road network, the travel time using *IQGA* is significantly lower than those of the three single evaluation index algorithms (*PA*, *SPA*, and *PSPA*).
- (3) When the road is unblocked, the proposed *IQGA* and the other algorithms have similar travel time. This is because *IQGA* takes into account the road conditions, the driver's own characteristics, oil consumption and other factors, rather than considering only a single index of travel time as the factor of route selection.
- (4) When the scale of the road network reaches a certain level as shown in Figure 4d, *IQGA* can still ensure real-time route selection due to its quantum parallel computing ability, while other multi-factor equilibrium algorithms (*WEA* and *RSGA*) have basically failed due to the enormous running costs.

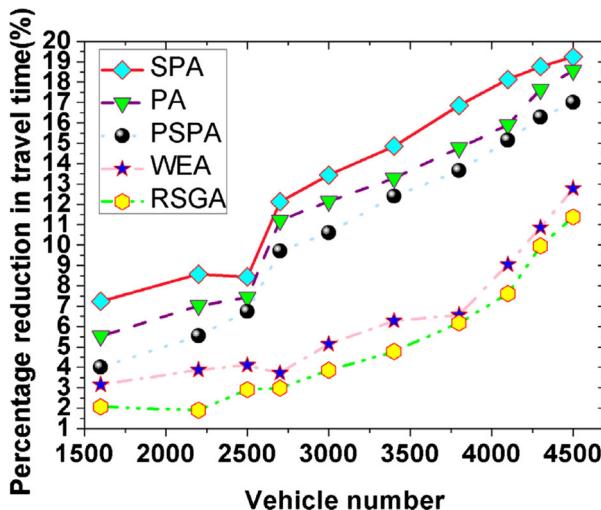
### 5.3 Real Urban Traffic Network

In order to verify the practicability of *IQGA*, we selected the road network of the Wuchang District in Wuhan City, and mapped it into the model as shown in Figure 5.

The real network includes twenty-four intersections and thirty-six two-way road sections, where there are five different traffic conditions: (1) the number of vehicles on all road sections are less than the threshold value of the road capacity; (2) the number of vehicles on parts of the road sections are greater than the threshold value and less than the congestion capacity, while those on the other sections are less than the threshold value of the road capacity; (3) the number of vehicles on parts of the road sections are greater than the congestion capacity, while those on the other sections are less than the threshold value of the road capacity; (4) the number of vehicles on parts of the road sections are greater than the congestion capacity, while those on the other sections are greater than the threshold value and less than the congestion capacity; (5) the number of vehicles on all road sections are greater than the threshold value and less than the congestion capacity. The corresponding results are shown in Figure 6.

**Figure 5** Mapping of real urban traffic network of Wuchang District in Wuhan City





**Figure 6** The percentages of the decrease in travel time of *IQGA* over the three non-cooperative algorithms and two state-of-the-art equilibrium algorithms in the real urban traffic network

From Figure 6, we can draw the following conclusions.

- (1) The performance of *IQGA* is still satisfactory in the real urban road network. When the number of vehicles on all road sections are less than the threshold value of the roads, the decrease in travel time using *IQGA* is just 2%. However, when the number of vehicles was increased to the extent that all road sections were congested, the decrease in travel time using *IQGA* reaches 15%, which proves that it performs better and is consistent with the conclusion obtained in the artificial road network experiment.
- (2) *IQGA* has a very good utility value enhancing effect when dealing with complex traffic congestion. Although the scale of the real road network is small, under the whole road congestion scenario, the decrease in travel time using *IQGA* still reaches 15%, which obviously improves the effect of alleviating traffic congestion. Although the scale of the selected road network is small, the covered region is also small, so the traffic complexity on each road section was not low. This further validates the effectiveness of using *IQGA* in dealing with complex traffic congestion scenarios.

## 6 Conclusions

In this paper, the *IQGA* method is proposed to solve the problem of traffic congestion in urban road networks, and experiments were carried out to validate the rationality, practicability, and robustness of the method through quantum computing simulations based on classical computers. In the process of designing the algorithm, this paper combines the problem and the algorithm, and proposes a strategy to initialize the algorithm according to the current state of the road sections. It ensures the diversity of the algorithm solution based on the combination with the actual problems, thereby increasing the possibility of obtaining an optimal solution. When using the mathematical representation to map the route selection, this paper presented a strategy to apply self-correction in backtracking and made full use of the iterative results of the

algorithm. This strategy ensures the relativity of temporary solutions in the iterative process, reduces the algorithm running times, and accelerates the appearance of an optimal solution. When a temporary solution to the corresponding problem is obtained using *IQGA*, this paper proposes a method to evaluate the temporary solution, which is to calculate the utility value of each selected route. The utility value calculation includes full consideration of the oil consumption, road conditions, and other factors, which considers the influencing factors to the greatest degree and is comprehensive and reasonable. In the iterative process, this algorithm proposes the *QUS* strategy, which can adaptively adjust the current iteration step according to the current results and is thus able to filter non-optimal solutions quickly to obtain an optimal solution as soon as possible. Finally, this study uses a classical computer to simulate a quantum computer to carry out the verification experiments on the artificial and real road networks. The conclusions of these experiments are as follows:

- (1) The performance of the *IQGA* method is high in dealing with complex road conditions, multi-sections, and multi-vehicles. Because the *IQGA* method has the characteristics of high parallel quantum computing and can carry out an operation on all qubits at the same time, it is suitable for processing large-scale data. The greater the number of vehicles, the more superior the algorithm is compared with conventional algorithms. The *IQGA* method is also a heuristic learning algorithm. Although the algorithm cannot guarantee that the final output is the optimal solution, the characteristics of learning allow the algorithm adjust more factors iteratively in order to deal with more complex problems. Statistical results are not sufficient when considering complex factors, so the greater the number of factors considered in the *IQGA* method, the more superior it is. When the number of the road sections in road network increases, and the routes to be selected increases, the change in the value of a quantum bit can cause a large change in the corresponding utility value. Under the superposition of the effects of a single section, the probability of the optimal solution obtained by the *IQGA* method is relatively high.
- (2) The *IQGA* method is not suitable for small scale, non-congested road networks. Although the quantum algorithm has the characteristics of high parallelism, the iterative cycles are still unable to parallel. In the small road network, the qubits of the quantum genetic chromosomes are few and the impact of the iterative update for route selection is small, so the performance of the quantum algorithm is not as good as the general navigation algorithms. Besides, in the non-congested traffic network, the road congestion coefficient is set as 1, which does not change with the number of vehicles. In such circumstances, the performance of the *IQGA* method in dealing with the traffic congestion problem is far less than the common route selection algorithms used on traditional computers, regardless of the running efficiencies or the final results.

The *IQGA* method proposed in this paper needs to be improved in the following two aspects.

- (1) In the algorithm, the quantum chromosomes are discarded when the cost threshold value and the preference threshold value are given, which destroys the correlation between generations. Therefore, this strategy can be further improved to continue the correlation between generations, and to reduce unnecessary computation.

- (2) The weather is not considered as a factor, and this may affect the preference value of the driver and the cost value. Therefore, more factors should be considered so that the simulation of the algorithm is closer to real world driving conditions encountered by a driver.

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## References

1. Arokhalo M Z, Selamat A, Hashim S Z M, et al. Route guidance system using multi-agent reinforcement learning[C]. International Conference on Information Technology in Asia. 2011, 1–5
2. Bezuglov, A., Comert, G.: Short-term freeway traffic parameter prediction: Application of grey system theory models. *Expert Systems with Applications*, Volume. **62**(15), 284–292 (November 2016)
3. Kit Yan Chan , Tharam Dillon , Elizabeth Chang , Jaipal Singh. Prediction of Short-Term Traffic Variables Using Intelligent Swarm-Based Neural Networks, *IEEE Transactions on Control Systems Technology* , Vol (21), no. 1, 2012, 263–274
4. Desai, P., Loke, S.W., Desai, A., et al.: CARAVAN: Congestion Avoidance and Route Allocation Using Virtual Agent Negotiation. *IEEE Trans. Intell. Transp. Syst.* **14**(3), 1197–1207 (2013)
5. Fernando, O., Nicolas, E.S.: Wardrop Equilibria with Risk-Averse Users [J]. *Transp. Sci.* **44**(1), 63–86 (2010)
6. Grivokostopoulou Foteini, Hatzilygeroudis Ioannis. An automatic marking system for interactive exercises on blind search algorithms. *Artificial Intelligence in Education - 16th International Conference, AIED: Memphis*. **2013**, 783–786 (2013)
7. Groot N, De Schutter B, Hellendoorn H. Toward System-Optimal Routing in Traffic Networks: A Reverse Stackelberg Game Approach [J]. *IEEE Trans. Intell. Transp. Syst.*, 2015, 16(1):29–40
8. He Zhonghe, Wang Li, Li Dai, Zhang Lingyu. Steady-State Signal Control for Urban Traffic Networks, 2015 IEEE 18th International Conference on Intelligent Transportation Systems, 15–18 Sept. 2015, 463–470
9. Jinghao, S., Lan, G., Deng, Q., Xin, Z., Yang, F.: Modeling Urban Traffic Control Systems from the Perspective of Real Time Calculus. *Journal of Software*. **27**(3), 527–546 (2016)
10. Kim Jisoo, Park Bumjin, Moon Byung-Sup, Eo Hyo-Kyoung. Improvement of bus arrival time estimation model by weighted moving average method. 21st World Congress on Intelligent Transport Systems, ITSWC: Detroit, September. 2014 (2014)
11. Kouvelas, A., Aboudolas, K., Papageorgiou, M., Kosmatopoulos, E.B.: A Hybrid Strategy for Real-Time Traffic Signal Control of Urban Road Networks, pp. 884–894. *IEEE Transactions on Intelligent Transportation Systems*, Sept (2011)
12. Lee Jeng-Wei, Lo Chun-Chih, Tang Shih-Pu, Horng Mong-Fong, Kuo Yau-Hwang. A hybrid traffic geographic routing with cooperative traffic information collection scheme in VANET, *Advanced Communication Technology (ICACT)*, 2011 13th International Conference on, 13–16 Feb. 2011, 1496–1501
13. Lipets, V., Vanetik, N., Gudes, E.: Subsea: an efficient heuristic algorithm for subgraph isomorphism. *Data Min. Knowl. Disc.* **19**(3), 320–350 (December 2009)
14. Liping, Y., Hu, W., Wang, H., Zhenyu, Q., Bo, D.: Dynamic Real-Time Algorithm for Multi-Intersection Route Selection in Urban Traffic Networks. *Journal of Software*. **27**(9), 2199–2217 (2016)
15. Liu, K., Yang, B., Shang, S., Li, Y., & Ding, Z. (2013). MOIR/UOTS: Trip Recommendation with User Oriented Trajectory Search. *IEEE, International Conference on Mobile Data Management* (Vol. 1, pp. 335–337). IEEE
16. Mingjun, W.: Meng Yu. Research on the optimal route choice based on improved Dijkstra. *Advanced Research and Technology in Industry Applications (WARTIA)*. IEEE Workshop, Ottawa. **2014**, 303–306 (2014)
17. Shinsuke Nakajima, Daisuke Kitayama, Yoshitaka Sushita, Kazutoshi Sumiya, Naiwala P. Chandrasiri, Kazunari Nawa, Route recommendation method for car navigation system based on estimation of driver's

- intent, Vehicular Electronics and Safety (ICVES), 2012 IEEE International Conference on, 24–27 July 2012, 318–323
- 18. Negulescu S C, Kifor C V, Oprean C. Ant Colony Solving Multiple Constraints Problem: Vehicle Route Allocation[J]. International Journal of Computers Communications & Control, 2008, iii (4), 366–373
  - 19. Ordóñez, F., Stier-Moses, N.E.: Wardrop equilibria with risk-averse users[J]. Transp. Sci. **44**(1), 63–86 (2010)
  - 20. Pan, J., Popa, I.S., Zeitouni, K., et al.: Proactive Vehicular Traffic Rerouting for Lower Travel Time. IEEE Trans. Veh. Technol. **62**(8), 3551–3568 (2013)
  - 21. Pandit, K., Dipak, G., Michael Zhang, H., Chuah, C.-N.: Adaptive Traffic Signal Control with Vehicular Ad hoc Networks, pp. 1459–1471. IEEE Transactions on Vehicular Technology, May (2013)
  - 22. Tomas Potuzak. Feasibility study of optimization of a genetic algorithm for traffic network division for distributed road traffic simulation, 2013 6th International Conference on Human System Interactions (HSI), 6–8 June 2013, 372–379
  - 23. Mahmood Rahmani, Erik Jenelius, Haris N. Koutsopoulos. Non-parametric estimation of route travel time distributions from low-frequency floating car data. Transportation Research Part C: Emerging Technologies, Volume 58, Part B, September 2015, 343–362
  - 24. Rhee Kyoung-Ah, Kim Joon-Ki, Lee Young-ihn, Ulfarsson Guðmundur F: Spatial regression analysis of traffic crashes in Seoul. Accid. Anal. Prev. **91**, 190–199 (June 2016)
  - 25. Sedeño-Noda, A., Raith, A.: A Dijkstra-like method computing all extreme supported non-dominated solutions of the biobjective shortest path problem. Comput. Oper. Res. **57**, 83–94 (May 2015)
  - 26. Shang, S., Ding, R., Yuan, B., Xie, K., Zheng, K., & Kalnis, P. (2012). User oriented trajectory search for trip recommendation. EDBT (pp. 156–167)
  - 27. Shang, S., Ding, R., Zheng, K., Jensen, C.S., Kalnis, P., Zhou, X.: Personalized trajectory matching in spatial networks. VLDB J. **23**(3), 449–468 (2014)
  - 28. Shang, S., Zheng, K., Jensen, C.S., Yang, B., Kalnis, P., Li, G., et al.: Discovery of path nearby clusters in spatial networks. IEEE Transactions on Knowledge & Data Engineering. **27**(6), 1505–1518 (2015)
  - 29. Shang, S., Liu, J., Zheng, K., Lu, H., Pedersen, T.B., Wen, J.R.: Planning unobstructed paths in traffic-aware spatial networks. GeoInformatica. **19**(4), 723–746 (2015)
  - 30. Shang, S., Chen, L., Wei, Z., Jensen, C.S., Wen, J.R., Kalnis, P.: Collective travel planning in spatial networks. IEEE Transactions on Knowledge & Data Engineering. **28**(5), 1132–1146 (2016)
  - 31. Shang, S., Chen, L., Wei, Z., Jensen, C.S., Zheng, K., Kalnis, P.: Trajectory similarity join in spatial networks. Proceedings of the Vldb Endowment. **10**(11), 1178–1189 (2017)
  - 32. Shang, S., Chen, L., Jensen, C.S., Wen, J.R., Kalnis, P.: Searching trajectories by regions of interest. IEEE Transactions on Knowledge & Data Engineering. PP(99), 1549–1562 (2017)
  - 33. Shang, S., Chen, L., Wei, Z., Jensen, C. S., Zheng, K., & Kalnis, P. (2018). Parallel trajectory similarity joins in spatial networks
  - 34. Sun, R., Ochieng, W.Y., Feng, S.: An integrated solution for lane level irregular driving detection on highways. Transportation Research Part c-emerging Technologies. **56**, 61–79 (2015)
  - 35. Tuberquia-David, M., Vela-Vargas, F., López-Chávez, H., Hernández, C.: A multifractal wavelet model for the generation of long-range dependency traffic traces with adjustable parameters. Expert Systems with Applications, Volume. **62**(15), 373–384 (November 2016)
  - 36. Wang Haizhong, Liu Lu, Qian Zhen, Wei Heng, Dong Shangjia. Empirical mode decomposition-autoregressive integrated moving average: Hybrid short-term traffic speed prediction model. Transportation Research Record, v 2460, n 1, 66–76, December 1, 2014
  - 37. Wang, S., Djahel, S., Mcmanis, J.: A Multi-Agent based vehicles re-routing system for unexpected traffic congestion avoidance, Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on. IEEE. 2541–2548 (2014)
  - 38. Wu, W., Yu, T., Tongdan, J.: A label based ant colony algorithm for heterogeneous vehicle routing with mixed backhaul. Applied Soft Computing. **47**, 224–234 (October 2016)
  - 39. Li Xiangling, Tao Xiaofeng, Liu Yinjun, Cui Qimei. Autoregressive model based data gathering algorithm for wireless sensor networks with compressive sensing. IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC, v 2015–December, Hong Kong, 2044–2048
  - 40. Xie, K., Deng, K., Shang, S., Zhou, X., Zheng, K.: Finding alternative shortest paths in spatial networks. ACM Trans. Database Syst. **37**(4), 1–31 (2012)
  - 41. Xie, K., Deng, K., Shang, S., Zhou, X., Zheng, K.: Finding alternative shortest paths in spatial networks. ACM Trans. Database Syst. **37**(4), 1–31 (2012)
  - 42. Xu, Y., Yuling, Z., Tingting, S., Yanfang, S.: Agent-Based Decentralized Cooperative Traffic Control Toward Green-Waved Effects. Journal of Software. **23**(11), 2937–2945 (2012)
  - 43. Yamada, K., Ma, J., Fukuda, D.: Simulation Analysis of the Market Diffusion Effects of Risk-averse Route Guidance on Network Traffic. Procedia Computer Science. **19**, 874–881 (2013)

44. Yang Jing. Routing method of quantum genetic algorithm. *Computer Modelling and New Technologies*, 2014, v18, n11, 178–181
45. Yang, B., Guo, C., Jensen, C. S., Kaul, M., & Shang, S. (2014). Stochastic skyline route planning under time-varying uncertainty. *IEEE, International Conference on Data Engineering* (Vol. 8, pp. 136–147). IEEE Computer Society
46. Yufei, Y., Duret, A., van Lint, H.: Mesoscopic Traffic State Estimation based on a Variational Formulation of the LWR Model in Lagrangian-space Coordinates and Kalman Filter. *Transportation Research Procedia*. **10**, 82–92 (2015)
47. Zheng, K., Shang, S., Yuan, N. J., & Yang, Y. (2013). Towards efficient search for activity trajectories. *IEEE, International Conference on Data Engineering* (pp. 230–241). IEEE
48. Zheng, K., Su, H., Zheng, B., Shang, S., Xu, J., & Liu, J., et al. (2015). Interactive Top-k Spatial Keyword queries. *IEEE, International Conference on Data Engineering* (Vol. 2015-may, pp. 423–434). IEEE
49. Zhu, S., Zhao, G., Zhao, G., Zhao, G., Wang, J.: Probabilistic routing using multimodal data. *Neurocomputing*. **253**(C), 49–55 (2017)